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Equilibrium fuel supply and carbon credit pricing under market competition and environmental regulations: A California case study

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HIGHLIGHTS

- Mathematical programming with equilibrium constraints method is used.
- Investigated simultaneous equilibrium on fuel supply market and carbon trade market.
- Studied interactions between commodity market and carbon trade market.
- Cellulosic biofuels play critical role in de-carbonization transport sector.
- Mathematically and empirically proves the relationship between carbon price and regulation.

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ABSTRACT

Performance-based environmental regulation has gained popularity as a policy tool to prevent climate change. California implements a Low Carbon Fuel Standard regulation to reduce the average carbon intensity of fuels by 10 percent, without specifying technologies to achieve the target. A carbon trading market is established to facilitate fuel producers making revenue by producing low carbon second-generation renewable fuels. There is a knowledge gap in understanding interactions between commodity and carbon trade markets under performance-based regulation. We propose a mathematical program with an equilibrium constraints model to find the equilibrium transportation energy portfolio under environmental protection policy. The model utilizes Karush-Kuhn-Tucker optimality conditions to represent the profit maximization of fuel suppliers. Profit is counted in both the commodity market and the carbon trading market. Our results show that carbon credit encourages the production of second-generation biofuels, which plays a critical role in the success of the Low Carbon Fuel Standard. Carbon credit price is driven by compliance with carbon intensity regulations, which we prove through mathematical formulation and empirical data analysis. Reducing carbon intensity is the key to promote biobutanol underperformance based on the low carbon fuel policy. The proposed framework, with small adjustments, can be used to evaluate performance-based regulation in other fields.

1. Introduction

The transportation sector, dominated by petroleum fuels, is a major cause of greenhouse gas (GHG) emissions worldwide [1]. In 2014, directly combusted GHG from the transportation sector contributed to 23% of energy-related GHG emissions globally [2], 26% in Europe [3], 33% in United States [4], and between 15% and 40% in major developing countries [5]. Due to concerns about air quality, energy security, and global climate change, countries around the world have developed various regulatory policies to promote the production of renewable energy to replace petroleum-based fossil fuel in transportation. For example, the European Union aimed to derive 20% of its energy from renewable sources by 2020, with 10% specifically in the transportation sector [6]. The Chinese government issued medium- and long-term plans to meet 15% of its primary energy demand with renewables by 2020 and 30% by 2030 [4]. In the United States, the national policy is the Renewable Fuel Standard (RFS) [7]. RFS requires a certain volume of renewable fuel to replace petroleum-based fuels. The target is 36 billion gallons of renewable fuels by the year 2022, of which 16 billion gallons must be second-generation biofuel, specifically cellulosic

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biofuel. In other words, RFS specifies the preferred technologies to achieve its environmental protection target. This type of policy is often referred as technology-based regulation (TBR) [8]. In contrast, California is the first worldwide to implement a performance-based renewable energy policy in transportation. The target is to reduce the carbon intensity (unit as g CO_2e per MJ) of transportation fuels by 10 percent by 2020 compared to the 2010 intensity, regardless of fuel technologies used to achieve the target [9]. The term "performance-based" refers to the fact that the policy does not give preference to or set quantity targets for specific fuel technologies. Instead it caps performance, i.e. average carbon emissions. Some types of market-based policy instruments will accompany performance-based regulation to ensure the achievement of the desired performance; one example is the "cap and trade" system for the industrial sector in the European Union, which gives production companies a cap and allowance in polluting emissions [10]. Another is China's new energy vehicle subsidy system for promoting sustainable transportation [11]. Similarly, the California government established a carbon credit exchange market for fuel providers to trade surplus carbon credit or balance carbon deficit [12]. This means that, under the Low Carbon Fuel Standard, transportation fuel suppliers compete simultaneously on the commodity market and the carbon credit exchange market. Performance-based regulation (PBR) has the advantage of decentralizing governance by giving firms greater flexibility to comply with regulations. But it also requires government monitoring and market involvement to ensure that regulation targets can be achieved accordingly [13]. Therefore, the success of performance-based regulation depends on understanding firms' performance and reactions under a market equilibrium context. In the case of California's Low Carbon Fuel Standard, it is equally critical to investigate the interactions between firms' competitions on the two markets (commodity and carbon credit exchange). Our extensive literature review shows that the impacts of renewable energy policies on the biofuel market and on societal welfare have been well studied. However, despite all these efforts, very few studies have examined the impacts of carbon trading in promoting renewable energy *and* its interactions with the commodity market. This is the gap our paper tries to bridge. Specifically, this paper has two purposes. First, we derive the economically balanced supply of transportation energy under a performance-based renewable energy policy. A particular focus is given to assessing the regulation's impacts on the production of advanced biofuels, i.e. cellulosic biofuel. Second, we analyze the influence of carbon intensity compliance on carbon credit price, which can further affect fuel suppliers' production decisions on high cost, low carbon, second-generation biofuels.

To conduct this analysis, we developed a mathematical program with an equilibrium constraints model (MPEC) to find the market equilibrium under low carbon policy. The model utilizes Karush-Kuhn-Tucker (KKT) optimality conditions to represent the profit maximization of fuel providers [14,15], where profits on both commodity trading and carbon credit exchanging are considered. The contribution of this paper is using the MPEC model to investigate optimal strategies on transportation energy supply and carbon trade. Existing studies primarily focus on just one of the two markets. Given that an increasing number of regions and countries are considering carbon credit trading, it is critical to understand the role of carbon credit trading in achieving environmental targets. We try to answer this question.

The remainder of this paper is organized as follows. Section 2 presents a comprehensive literature review on biofuel economy, policies, and state-of-the-art analysis methods. In Section 3, we present the assumptions, notations and formulation of a non-cooperative market competition model. A solution approach is introduced that transforms the original multi-agent profit maximization problem into a solvable MPEC model. Section 4 illustrates analysis results, discussions, and relevant policy implications based on the California Low Carbon Fuel Standard case study. Finally, the main findings of this study are summarized and conclusions are drawn in Section 5.

2. Literature review

Existing environmental protection regulations can be classified into two types, i.e. technology-based regulation (TBR) and performance-based regulation (PBR). TBR defines statutes set the level of regulation by determining what kinds of controls are technologically achievable for a particular regulated industry, which usually means specific quantitative requirements for each feasible technology [16]. Examples of TBR include predefined national transportation biofuel production levels from 2008 to 2022 listed in the United States Renewable Fuel Standard (RFS) [8], or setting sales targets for electric or hydrogen fuel cell vehicles in California's Zero Emission Vehicle program [17]. A report from the Government Accountability Office claimed that the RFS is not meeting expected greenhouse gas reductions because second-generation biofuels are not being produced to the levels specified in the regulation [18]. RFS regulation mandates the cumulative production quantity of cellulosic ethanol, one type of second-generation biofuel, to reach 16 billion gallons by the year 2022. The failure of RFS is because technology-based regulation generally cannot accommodate technology or market changes and discourages efficient use of resources [19]. PBR refers to the implementation of rules, including explicit financial incentives, which encourage regulated firms or market to achieve certain performance goals, while affording the firms significant discretion in how the goals are achieved [16]. PBR policy has the advantage of flexibility and is able to harness the economic self-interest of participants in the market. PBR has gained popularity in regulated industries. This study intends to evaluate, in the short term, the effectiveness of performance-based market mechanisms in promoting second-generation biofuels.

Economic equilibrium theories and optimization methods have been used to estimate the impacts of renewable energy policies on biofuel production and its environmental implications. The first wave of research was around the 2008 economic recession, when petroleum-based energy prices were high; most of these studies focus on how to economically expand renewable biofuel production. Banos et al. [20] summarized major optimization methods used in bioenergy research during that period. For example, Tyner and Taheripour [21] conducted a firm-level ethanol refinery production analysis and mathematically determined the break-even corn and ethanol prices under various profit conditions. Rajagopal et al. [22] built a partial equilibrium multi-market framework to model the competition between supply and demand in food and fuel markets. Chen et al. [23] investigated the food-versus-biofuel trade-off by comparing losses and gains in consumer surplus in different socioeconomic sectors. Yue et al. [24] reviewed the key challenges and opportunities in the modeling and optimization of the biomass-to-bioenergy supply chain, specifically examining how to incorporate the spatial-specific bio-refinery processes and temporal-specific operations into multi-scale modeling and optimization of biofuel production. After the first wave of research, more recently, bioenergy research has focused on assessing the environmental and social welfare benefits of bioenergy through government intervention. Chen and Fan utilized a system-perspective deterministic [25] and stochastic programming [26] models to study the optimal fuel supply pathway to satisfy California's Low Carbon Fuel Standard, which aims at reducing 10% of greenhouse gas emissions from the transportation sector by 2020 compared to 2010 levels. Moncada et al. [27] analyzed the optimal biofuel production and production capacity expansion strategies in Germany from 1992 to 2014. Jin and Illukpitiya [28] proposed a model to optimally determine the harvesting unit for ethanol biorefineries and to estimate harvesting, storage and transportation costs of a type of biomass, switchgrass, under various harvesting schedules. Zhai et al. [29] utilized a game-theoretic approach to model and analyze the government's policy-choosing and its implications for the optimal biomass power supply. The model was formulated based on a sequential game with asymmetric information between three players, i.e. the farmer, the biomass power plant, and the government. Huang

and Hu [30] built an agent-based model to study the social optimal biomass supply price and policy making in the biofuel industry. Specifically, the agents include farmers and one biofuel producer, who are aiming to reach profit maximization through a bi-level decision-making structure. Chen et al. [31] developed a dynamic programming model to design yearly biofuel production levels to satisfy government-regulated environmental targets. The dynamic component lies in the determination of advanced biofuel production costs, which is a function of cumulative biofuel production.

Another school of literature focuses on investigating mechanisms to improve biofuel production, such as mandating biofuel production levels, production credit trading, etc. For example, McPhail and Babcock [32] evaluated impacts of biofuel mandates on the corn and ethanol industries with different economic models. Thompson et al. [33] employed a stochastic structural model aiming to understand the impacts of ethanol-mandated production on ethanol price under different petroleum price and corn yield scenarios. Lapan and Moschini [34] developed a framework to find the optimal biofuel production mandates and subsidies in terms of social welfare. Chen and Li [35] developed a dynamic, multimarket model to derive the economically viable supply of agricultural biomass under various price and advanced biofuel feedstock scenarios. The model also considered impacts of biomass production on the maintenance cost of the Conservation Reserve Program, which will influence biomass availability. Mason and Wilmot [36] investigated the trading market of Renewable Identification Numbers (RINs) under the United States Renewable Fuel Standard. They tried to model the statistical variations of the price in response to uncertainties in government policy and demonstrated that a better understanding of the RINs price can have a non-trivial effect on biofuel production and infrastructure expansion decisions.

The above studies on biofuel policy and optimization have not captured the interactions between the commodity market and the carbon trade market. Specifically, how does the price of carbon credits influence the quantity of renewable biofuel production under performance-based regulations? This paper aims to fill this knowledge gap by formulating a mathematical programming model that simultaneously solves for equilibrium in two separated but connected markets, i.e. the energy commodity and carbon trade markets. In the literature, there are several methods to model market competition and equilibrium. The most direct method is to analytically solve for the competitive equilibrium solutions in one market/player and plug it into formulations for the other market and players. Huang and Chen [37] chose this approach to study the strategic behavior in an imperfectly competitive cellulosic biofuel supply chain. They solved the equilibrium among stakeholders in a multi-echelon supply chain by solving a collection of first-order conditions associated with players' profit-maximization problems. The direct solution approach works better when players are making maximized profit from one market, i.e. commodity trading, and when one player's decisions have little or no impact on other players. Thus, it is not suitable in this study because we try to model commodity trade and carbon trade simultaneously. Another method is the Stackelberg leadership model, which mathematically models the market mechanism in which a leader firm moves first and then the follower firms move sequentially. Bai et al. [7] adopted this method to investigate the spatial equilibrium of a biofuel-feedstock supply chain with participants from a leader biofuel manufacturer and a follower farmer. This model works best in a single-leader multiple-follower market structure. This is not the structure in our study, where each biofuel producer and importer share equal information and make decisions that influence each other directly or indirectly. We choose to utilize Karush-Kuhn-Tuck (KKT) transformation to convert the market equilibrium problem into a cluster of KKT first-order optimality constraints and then solve a mathematical programming with equilibrium constraints (MPEC) problem. This approach is suitable here because of the linear demand curve assumption and convex feature profit function. Thus first order KKT conditions can always be found.

In this paper, our goal is not to improve the methodology; instead, we aim to show how this novel mathematical formulation can be used to model the optimal fuel supply problem under environmental policy and carbon trade mechanisms, while taking into account the non-cooperative behavior of market participants.

The above literature about biofuel market modeling mainly focuses on bioethanol and biodiesel, which currently have or are expected to have large volume production in the short term. These biofuels are expected to play major roles in low carbon transportation fuel policies in the U.S. [12], Canada [38], the European Union [39], and major developing counties [40]. But there are other biofuels that could potentially help achieve low carbon fuel targets. Methanol has been promoted as an alternative and low carbon transportation fuel from time to time over the past fifty years. Methanol has not become a substantial fuel because of its introduction in a period of rapidly falling petroleum prices and because it lacks strong advocacy [41]. Another type of biofuel for the transportation sector is butanol. Butanol is an alcohol that can be produced through a petrochemical or fermentative process. It has a comparable energy density to gasoline, which is higher than those of bioethanols. One study showed that blending butanol and gasoline has advantages in terms of cost and emissions [42]. In 2018, the U.S. Environmental Protection Agency approved butanol as a gasoline additive at up to 16% volume ratio. Thus, there is now an increasing interest in biobutanol. But butanol's use in transportation fuel is still limited because of several limitations such as low production rate, higher GHG emissions per energy unit compared with bioethanol, compatibility issues with internal combustion engines, etc. [43]. In our study, in addition to the major biofuels, i.e. biodiesel and bioethanol, considered by low carbon fuel policies, we will also try to evaluate the impacts of other biofuels, particularly biobutanol, on achieving a low carbon fuel portfolio.

3. Methodology

The objective of this paper is to develop a modeling framework to investigate renewable fuel production strategies and carbon exchange strategies under market equilibrium for achieving sustainability targets. Major regular petroleum and renewable energy technologies are included in the model. We assume that each player is producing one type of energy technology.[1] There are mainly three biomass-based renewable fuels, i.e. corn, sugarcane, and cellulosic, which are made into ethanol to blend with pure gasoline (called CARBOB in the regulation). The three fuels have different production costs and carbon intensities.[2] Therefore, competition between renewable biofuels is essentially about resource relocation, because the government regulates the maximum of biofuel (i.e. ethanol) content in gasoline to be 15%, with 20% for diesel. In addition, each renewable fuel can generate a different carbon credit/deficit that can be traded in a carbon credit exchange market. Carbon credit/deficit is generated based on the difference between a fuel's carbon intensity and carbon intensity compliance. In each regulation year, a fuel producer needs to balance off its carbon deficit, if there is any, by purchasing carbon credit from producers who have a carbon credit surplus. In our model, each fuel producer will maximize its

[1] We acknowledge that this assumption simplifies our model. However, the focus of this paper is the competition between heterogeneous fuel producers on the commodity market and carbon trade market, rather than competition within homogeneous fuel producers. Adding competition within same fuel technologies will be a future research direction of this paper.

[2] We have to clarify that although we used the term "production cost," sugarcane ethanol is mainly imported rather than produced in USA. According to the US Department of Energy data [44], US domestic production accounts for more than 80% of energy consumption for all fuel types, except sugarcane ethanol. Data shows that 95% of sugarcane ethanol is imported from Brazil. Thus, in this model, the production cost for sugarcane ethanol is actually the import cost.

Table 1
Notation and description.

Sets	
$T = \{t\}$	index set of time periods (years)
$R_G = \{r_g\}$	index set of renewable gasoline substitutes {corn ethanol, sugarcane ethanol, cellulosic ethanol, pure gasoline (CARBOB)}
$R_D = \{r_d\}$	index set of renewable diesel substitutes {ultra-low sulfur diesel, biodiesel, renewable diesel}
$F = \{f\}$	index set of all types of transportation fuel {R_G, R_D, electricity, hydrogen}
Parameters	
I_f	index set of carbon intensity value for transportation fuel f (g CO_2e per gallon)
ρ_f	index set of energy intensity value for transportation fuel f (MJ per gallon)
B_G, B_D	Maximum renewable fuel blend percentage, 15% for gasoline and 20% for diesel.
A_G^t, A_D^t	Mandatory cap for gasoline and diesel average carbon intensity in year t (g CO_2e per MJ)
M_G^t, M_D^t	Demand for gasoline and diesel fuels in year t (GGE per year)
$P_f = f_f(q_f)$	Inverse demand function for fuel type f, where P_f and q_f denote the price ($ per gallon) and quantity respectively
C_f^t	Exogenously determined unit production cost of fuel f in year t ($ per gallon)
P_R^t	Unit price for carbon credit ($ per Metric Ton CO_2e)
Decision variables	
q_f^t	Production quantity of fuel type f
$x_{ff'}^t$	Quantity of carbon credit exchanged from fuel producer f to f'

production profit (revenue minus production cost) plus its carbon trade profit or deficit. We utilized Karush-Kuhn-Tuck (KKT) transformation to convert the profit maximization problem of each fuel producer into sets of constraints. The market equilibrium is found when all profit maximization constraints are satisfied. In the rest of this section, we will introduce the notation and model formulation first, then discuss input data.

4. Notation and model formulation

The notation used in the model is presented below (see Table 1):

Given the above notation, the following model determines the quantity and mix of transportation fuel produced, and the exchange of carbon credit between different fuel producers at each modeling year t.

As explained earlier, we assume that each player is producing one type of fuel, denoted as f. Therefore, for each fuel producer, it solves one profit optimization problem as follows:

$$\max P_f^t * q_f^t - C_f^t * q_f^t + P_R^t * X_f^t = f_f(q_f) * q_f^t - C_f^t * q_f^t + P_R^t * \left(\sum_{f' \in F/f} x_{ff'}^t - \sum_{f' \in F/f} x_{f'f}^t\right) \quad (1)$$

$$s.t.\ q_f^t * (A_f^t - I_f) \geq \left(\sum_{f' \in F/f} x_{ff'}^t - \sum_{f' \in F/f} x_{f'f}^t\right) \quad (2)$$

$$q_f^t \geq 0,\ t \in T, f \in F; x_{ff'}^t \geq 0,\ t \in T, f \in F, f' \in F/f \quad (3)$$

The objective function (1) represents the profit of each fuel producer. It contains three components, i.e. fuel production revenue, fuel production cost, and the revenue or cost of selling or purchasing. The demand for fuel type f is endogenously determined by production quantity, i.e. follows a type of inverse demand function $f_f(q_f)$. The production cost of fuel f is assumed to be exogenously determined as C_f. The $X_f^t = \left(\sum_{f' \in F/f} x_{ff'} - \sum_{f' \in F/f} x_{f'f}\right)$represent the net carbon credit sell (positive) or purchase (negative) by fuel producer f. The subject Eq. (2) is to ensure the balance of carbon credit for each fuel producer. When the produced fuel f has a carbon intensity that is lower than the mandated level, the Eq. (2) will force $\left(\sum_{f' \in F/f} x_{ff'} - \sum_{f' \in F/f} x_{f'f}\right)$ to be positive (sell carbon credit). On the other hand, when fuel f has a higher than mandated level carbon intensity, $\left(\sum_{f' \in F/f} x_{ff'} - \sum_{f' \in F/f} x_{f'f}\right)$ will be negative (purchase carbon credit).

We further assume that the inverse demand function follows a linear format, i.e. $f_f(q_f) = a_f - b_f * q_f$. Because the objective function is convex and continuous on decision variables q_f^t, $x_{ff'}^t$, the above optimization problem is equivalent to the following Karush-Kuhn-Tucker (KKT) optimality conditions, for all $t \in T$:

$$0 \leq (C_f^t - f_f(q_f^t) - f_f'(q_f^t) * q_f^t - \lambda_f^t * (A_f^t - I_f)) \perp q_f^t \geq 0,\ \forall f \in F \quad (4)$$

$$0 \leq (\lambda_f^t - P_R^t) \perp x_{ff'}^t \geq 0,\ f \in F,\ \forall f' \in F/f \quad (5)$$

$$0 \leq \left(q_f^t * (A_f^t - I_f) - \left(\sum_{f' \in F/f} x_{ff'}^t - \sum_{f' \in F/f} x_{f'f}^t\right)\right) \perp \lambda_f^t \geq 0,\ \forall f \in F \quad (6)$$

where λ_f^t is the Lagrange multiplier associated with constraint (2), the use of operator '$a \perp b$' denotes the complementarity condition $a \cdot b = 0$, and $f_f'(q_f^t)$ is the derivative of $f_f(q_f^t)$ with respect to q_f^t.

Eqs. (4)–(6) is the KKT representation of the profit maximization problem shown in Eqs. (1)–(3) for each player or fuel producer. Combining (4)–(6) of each fuel producer, we can find the equilibrium status of the market when each fuel producer can maximize its profit. There are additional constraints as follows:

$$\sum_{f \in Gasoline, R_G} q_f^t \geq M_G^t,\ \sum_{f \in Diesel, R_D} q_f^t \geq M_D^t,\ t \in T \quad (7)$$

$$\frac{\sum_{f \in R_G} q_f^t}{\sum_{f \in Gasoline, R_G} q_f^t} \leq B_G,\ \frac{\sum_{f \in R_G} q_f^t}{\sum_{f \in Diesel, R_D} q_f^t} \leq B_D,\ \forall t \in T \quad (8)$$

Eq. (7) is to ensure that the supply of fuel in the gasoline and diesel categories meets its demand in each year. Eq. (8) is the blend wall constraint which is the maximum blending rate of gasoline or diesel substitutes allowed to blend in gasoline or diesel, as mandated by the Environmental Protection Agency.

Therefore, any solution set that satisfies Eqs. (4)–(6) for each fuel producer and (7) and (8) for all fuel producers, is the market equilibrium solution for this problem. There is no nominal objective function because the maximum profit objective function for each fuel producer is transferred to equivalent KKT optimality constraint. The combination of all KKT constraints leads to market equilibrium.

4.1. Data collection

The proposed models are to determine the equilibrium production quantities of fuels and carbon credit price under California's Low Carbon Fuel Standard regulation. Table 2 shows input parameters adopted in the model. We have to acknowledge the limitation of input data and assumptions. Given that the major focus of this paper is to demonstrate the methodology instead of proving representative of input data, we can always improve input data when more data and market knowledge are available.

Note that for the demand curve of each fuel, Anderson and Coble [45] developed an approach to estimate the coefficients of linear and static demand curves for corn ethanol. We utilized their approach and available data for other fuels, with the exception of electricity and hydrogen. We adopted the projected electricity and hydrogen consumption of the California Vision 2.1 model, which satisfies the energy

Table 2
Model input parameters.

	Parameter	Value	Unit	Source
Demand, M^t_G, M^t_D	Gasoline Category	13.9–14.6	Billion Gas. Gal. Eq. (GGE)	[46]
	Diesel Category	4–4.2	Billion GGE	[46]
Carbon Intensity, I_f	R_G, R_D, gasoline, diesel, electricity, H_2	20–100	gram CO_2e/MJ	[9,47]
Energy Intensity, ρ_f	R_G, R_D, gasoline, diesel, hydrogen	89–150	MJ/Gallon	[9,47]
	Electricity	3.6	MJ/kWh	[9,47]
Technology, B_f	Ethanol blend wall	15%	%	[13,16]
	Biodiesel blend wall	20%	%	[19,48]
Regulation, A^t_G, A^t_D	Gasoline Category	96–88	gram CO_2e/MJ	[9]
	Diesel Category	95–91	gram CO_2e/MJ	[9]
Production Cost, C^t_f	Gasoline	2.6–2.8	2017 $/Gallon	[49][1]
	Corn ethanol	2.2–2.3	2017 $/Gallon	[50]
	Sugarcane ethanol	1.5–1.6	2017 $/Gallon	[51][2]
	Ultra-low sulfur diesel	3–3.3	2017 $/Gallon	[49]
	Biodiesel	3.9–4.2	2017 $/Gallon	[50]
	Electricity	0.091	2017 $/kWh	[52]
	H_2	4–6	2017 $/Gallon	[53][3]
Demand Curve, $P_f = f_f(q_f)$	Each fuel type f, except hydrogen and electricity			[45,46]

[1] Production cost is derived by subtracting a historically average profit margin of the refinery industry, 14% as reported by the US Census Bureau [49], from the forecasted retail price of gasoline in the Pacific region from 2017 to 2020 [54]. This derivation process is consistent with the methodology used by CARB [9].

[2] Sugarcane ethanol is mainly imported rather than produced in the US. The production cost of sugarcane refers to import cost, for which the International Energy Agency provides trade cost information in a recent (2017) report [51].

[3] Note that NREL's estimation has a unit of $ per 1 kg of hydrogen, and the conversion factor is 1 kg hydrogen equals 1 gasoline gallon equivalent (GGE), which is the same conversion factor used in hydrogen fuel cell studies.

demand for the remaining fuels [46].

4.2. Model solution and algorithm

This model is solved by AMPL software with CONOPT solver [55]. In order to find the profit maximization of each fuel market participant and the equilibrium status, we utilized KKT transformation to convert the profit maximization problem of each fuel producer into sets of KKT optimality constraints. These constraints turn out to be quadratic rather than linear and thus cannot be solved by the basic solver in AMPL, which is only good for linear programming. CONOPT is a solver designed to solve nonlinear programming problems and can accommodate both nonlinear functions in objective and in constraint functions [56]. In the model formulation listed above, no objective is specified; rather a set of KKT optimality constraints are listed. The CONOPT solver seeks a solution point that satisfies given constraints and finds the equilibrium.

5. Results and discussion

The proposed MPEC model solves for equilibrium production for each energy supplier in the market. Each market participant's objective is to maximize its own total profit of selling energy and selling/buying carbon credit. Three ethanol producers of different resources, i.e. corn, sugarcane (importer, not producer), and cellulosic, compete with each other on the commodity market, because of the 15% ethanol blend wall in gasoline. From an economic point of view, cellulosic ethanol cannot compete with corn ethanol. But due to carbon intensity compliance and the carbon trading market, cellulosic ethanol might be competitive if profits on the two markets are counted.

5.1. Model results

Fig. 1 presents the portfolio of transportation energy and carbon intensity under market equilibrium from 2015 to 2020. One general observation is that the volume of pure gasoline (referred to as CARBOB in the regulation) gradually decreases while alternative fuels increase in order to satisfy carbon intensity compliance as defined in California's Low Carbon Fuel Standard. In the category of gasoline and gasoline substitutes, corn ethanol volume is constantly decreasing over this time period while sugarcane ethanol's volume expands, until 2018 when the trend reverses. Only cellulosic ethanol is constantly growing, with significant expansion in 2019 and 2020. When LCFS starts getting more stringent, it requires low carbon cellulosic ethanol to balance the average carbon intensity of the fuel portfolio. In the diesel and diesel substitutes category, the supply of biodiesel grows from 2015 to 2018, then plateaus after 2018. This is mainly due to the blend wall of diesel, which is 20% in the model. For carbon intensity, the results show that the model's average carbon intensity for the diesel category is constantly lower than carbon intensity compliance requirements. For the gasoline category, the modeled carbon intensity is higher than the compliance value for each year, but the gap diminishes closer to the year 2020. Clearly, the diesel market provides a large amount of carbon intensity credits to the gasoline market to meet compliance. Thus, diesel fuels are critical to the success of the Low Carbon Fuel Standard regulation.

We speculate some explanations for this market equilibrium fuel portfolio. The transportation energy demand is in the unit of gasoline gallon equivalent (the same unit as defined in California's EMFAC and Vision 2.1 model), but LCFS's average carbon intensity is based on the unit of gram CO_2e per MJ. Therefore, a fuel supplier's profit maximization and its equilibrium will take into consideration the cost per gasoline gallon equivalent of each type of fuel as well as the energy stored in each gallon of fuel, i.e. energy intensity. Since CARBOB has the lowest production cost per MJ, the model chooses to use as much as possible as if there were no carbon compliance. However, as compliance value gets lower over time, low carbon biofuels (sugarcane or cellulosic ethanol) gradually play important roles in the fuel pathway. Corn ethanol has the lowest cost but a carbon intensity value as high as that of CARBOB. Cellulosic ethanol has the lowest carbon intensity but highest cost because it is still a new technology. Sugarcane ethanol's cost and carbon intensity are in the middle compared to the other two biofuels. Therefore, it is expected that corn ethanol is always preferred in the fuel portfolio whenever environmental constraint is not a concern. When carbon compliance starts to be implemented but not quite stringently, sugarcane becomes attractive because of its relative low cost and moderate carbon benefit. Finally, when compliance is stringent, such as after 2018, a large volume of cellulosic ethanol has to be produced to balance carbon intensity to meet compliance. This explanation is consistent with observations in the model results as shown

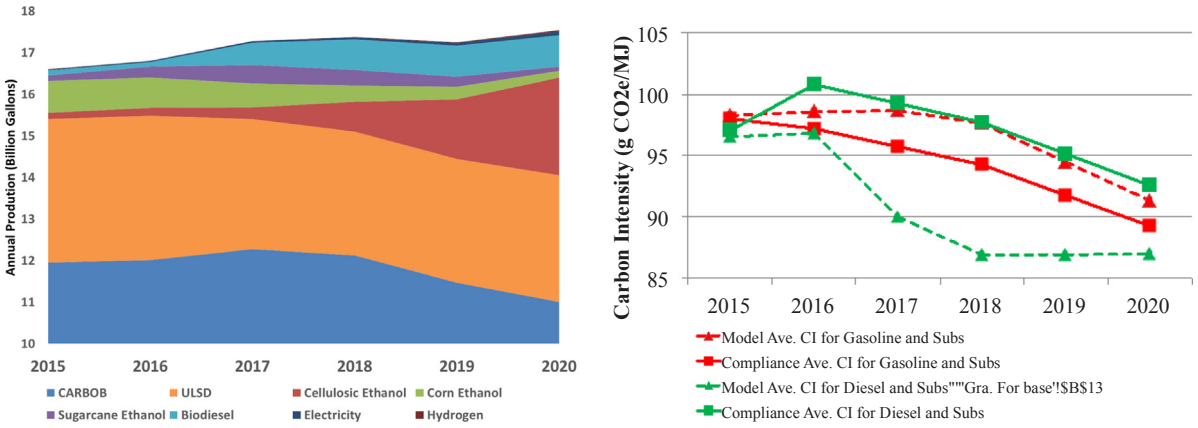

Fig. 1. Transportation energy portfolio (left) and carbon intensity (right) under equilibrium.

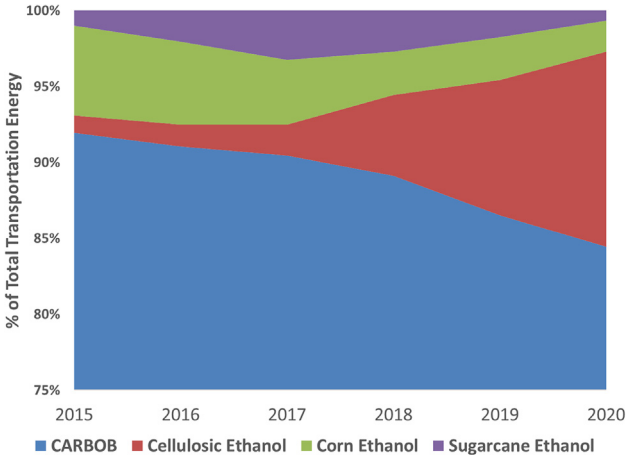

Fig. 2. Portfolio of gasoline and gasoline substitutes.

in Figs. 1 and 2.

5.2. Model validation with actual market data

We compared our modeled fuel portfolio with actual fuels supplied in the California market from 2015 to 2017 in Fig. 3. The actual market data is from Yeh et al. [12]. We observed that our model's results correctly predict the trend of biofuels but the magnitude of our prediction is smaller than the actual values that emerged in the market. For example, in our simulation, corn ethanol's volume decreased from 760 to 670 million gallons from 2015 to 2017. In the actual market, corn ethanol experienced a similar decreasing trend, but the exact number is larger than the numbers in our paper [12]. Similar findings are observed for sugarcane and biodiesel. One possible explanation is that, in our model, carbon credits can be used only in the year they are generated. However, in reality, fuel suppliers are allowed to bank carbon credits for future use or trading. In the early years of LCFS regulation (2011–2013), a large amount of carbon credit was generated because of the high carbon intensity compliance [12]. This allows the market to produce more low cost but high carbon intensity CARBOB and less biofuels in later years. But increasingly stringent carbon intensity compliance drives the supply of low carbon biofuels to grow. This matches the observed difference in magnitude and similarity in trend between model estimation and actual market performance.

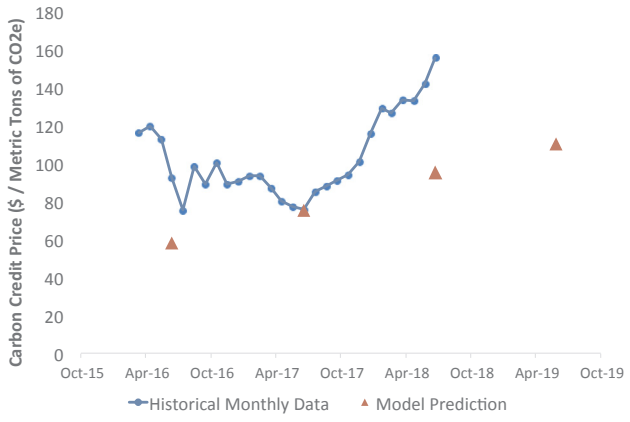

Fig. 3. Historical vs. model-predicted carbon credit trade price.

We compare our modeled carbon credit price with actual market price in Fig. 3. In the real carbon trade market, the price fluctuated around \$90 per metric ton of CO_2e from 2016 to the end of 2017, then rapidly climbed up to around \$130 for the first half of 2018, and finally reached around \$155 per metric ton of CO_2e in June 2018. Our model predicts a similar trend but with lower magnitude. Specifically, our model predicts the carbon price to be around \$60 per metric ton of CO_2e for 2016 and 2017, then \$100 in 2018 and \$120 in 2019. The consistency in trends between historical data and model prediction is expected, because a major driver of carbon credit price is carbon intensity compliance. The average carbon intensity compliance is at 98 g CO_2e/MJ from 2013 to 2015, and then the compliance rate is reduced by 1.5% each year from 2016 to 2018 and 2.5% for 2019 and 2020 respectively. The variation between actual and predicted carbon price is consistent with the increasingly aggressive compliance regulation. It is worth noting that carbon price was fluctuating around \$90 per metric ton of CO_2e for 2016 and most of 2017, even though 2016 is the year carbon intensity compliance started to decrease. Our explanation is that a large number of carbon credits were generated before 2015, when compliance was easy to meet (this was confirmed by Yeh et al. [12]). These carbon credits were banked and began being traded during 2016 and 2017, which kept the carbon price around \$90. However, since our model does not allow the banking of carbon credit, it predicts that the carbon credit price will continuously increase when compliance becomes more stringent at a similar rate. There might be various reasons for our model predicted carbon credit price lower than actual values. This will be topics for future studies to investigate detailed explanations and further improve our model.

5.3. Comparison with system optimal approach

Equilibrium approach is a useful way to investigate market competition and performance under environmental regulations. Another is system approach. This approach assumes a system planner who can control the production of each energy supplier. The purpose of the

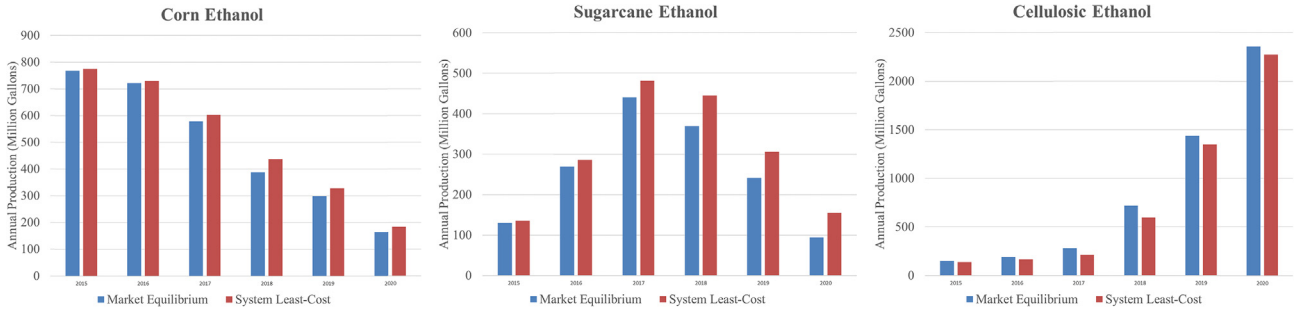

Fig. 4. Comparison of corn (left), sugarcane (middle), and cellulosic (right) ethanol production in market and system cases.

system planner is to provide transportation energy while satisfying environmental responsibility using a least-cost fuel portfolio. This least-cost solution considers only the production cost of transportation energy because production cost is the only cost to the system. Whether commodity trades between consumers and suppliers or carbon credit trades between suppliers, these are zero-sum trades. Noting that, we do not consider consumer surplus or production surplus in this study, but rather focus exclusively on explicit monetary costs.

We compare transportation energy portfolios under the system least-cost case and the market equilibrium case. Fig. 4 presents the production levels of corn (left), sugarcane (middle), and cellulosic (right) ethanol in the two cases. The system least-cost approach leads to less production of cellulosic ethanol. The difference tends to enlarge initially and then diminish after the year 2019. Here are some of our explanations. Though cellulosic ethanol has the lowest carbon intensity among all fuels, it also has the highest production cost in terms of volume ($ per gallon) or energy ($ per MJ). Thus, the system planner avoids producing cellulosic ethanol unless to satisfy environmental compliance. But in the market equilibrium case, the producer of cellulosic ethanol can obtain revenue from both the commodity and carbon trading markets. It can produce even when its marginal production revenue is below marginal cost, because the negative revenue is offset by profits from carbon credit trading. This explains the observation that cellulosic ethanol is produced at a higher level in the market equilibrium case than in the system case. As compliance gets more aggressive, such as in the years 2019 and 2020, environmental constraint as well as the blend wall constraint (15% ethanol blend rate) become the major constraints for both cases. Hence, as observed in the two cases, the majority of that 15% ethanol must come from cellulosic in order to meet compliance.

It is also observed that more sugarcane ethanol is imported in the system case between 2015 and 2017. Sugarcane ethanol has higher carbon intensity than cellulosic, but is still 30% lower than compliance. In order to achieve least production cost, the system planner used sugarcane ethanol as an interim solution during 2015–2017, before cellulosic ethanol dominated the ethanol market after 2018. But in the market equilibrium case, sugarcane ethanol faces competition from cellulosic ethanol because of the higher carbon credit profit cellulosic ethanol can generate with the same volume of production. The production quantity gap between the two cases gradually decreases after 2018. A similar pattern is observed for corn ethanol. In both cases, corn ethanol production is gradually reduced because of its high carbon intensity. In the system case, corn ethanol is produced at the maximum as long as the portfolio's average carbon intensity is maintained at compliance level. But in the market equilibrium case, corn ethanol's high carbon intensity means less carbon credit revenue; thus corn ethanol is produced at lower levels to maintain a higher selling price of corn ethanol for profit maximization.

Through the above comparison, we find that the carbon credit market encourages more production of low carbon intensity fuel, i.e. cellulosic ethanol, by internalizing the environmental externality of transportation fuels.

5.4. Implications of biobutanol on the transportation fuel portfolio

In the literature review section, we acknowledged that this study mainly focuses on bioethanol and biodiesel, which are expected to play major roles in low carbon transportation fuel policies in the U.S. [12], Canada [38], the European Union [39], and major developing counties [40]. Biobutanol is a promising biofuel with advantages and disadvantages. In this subsection, we assess implications of biobutanol on the transportation fuel portfolio. Specifically, in our model, we add biobutanol as one of the gasoline substitute fuel types, which makes it possible to be blended with CARBOB (pure gasoline) with the 16% volume ratio limit recommended by U.S. Environmental Protection Agency. The energy density of biobutanol is 110.53 MJ/gallon [27], which is lower than the energy density of gasoline, but higher than those of bioethanol. The carbon intensity of biobutanol needs to be based on life cycle analysis. Wu et al. [57] evaluated the life cycle energy and GHG emissions of biobutanol as a transportation fuel. Based on various production processes, its GHG emissions are different. Without losing generality, we choose the reported average value, i.e. 108.83 g CO_2e/MJ, as the carbon intensity for biobutanol. This is significantly higher than the carbon intensity values of bioethanol (20.4, 69.5 and 91.0 g CO_2e/MJ for cellulosic, sugarcane and corn ethanol), and higher than that of gasoline, 95.86 g CO_2e/MJ. Butanol is still not at the stage of industrial scale mass production; thus its production cost is high and its future is uncertain [58]. Currently, butanol is selling at $1–2 per kg,[3] which converts to $3.1–6.2 per gallon, based on its volumetric density. Assuming a 25% profit margin for the refinery industry (which is higher than the 14% profit margin for the petroleum refinery industry), we build two butanol cost scenarios at $2.3 and $4.7 per GGE. For the demand curve, since very little demand data exists for butanol, we assume that its demand curve has a form similar to that of cellulosic ethanol (since both are new technologies) but adjust the demand curve parameters based on the cost difference of the two biofuels. We acknowledge that there might be more suitable values for the cost and demand parameters of butanol, but given its uncertainties on the biofuel market, and since the objective of this study is focusing on building a novel mathematical model, we can improve the parameters when more information and knowledge are available.

We show the biofuel portfolio results in Fig. 5. Because current developments mainly use biobutanol as a gasoline additive with the recommended 16% limit, we present only the portfolio of gasoline substitute fuels, i.e. bioethanol and biobutanol. The results show that, in the $4.7 per gallon cost scenario, there is no biobutanol production. One advantage of butanol is its high energy density, which is 45% higher than that of ethanol. The model has an energy content demand (in MJ) constraint; thus all other things being equal, it will prefer fuel with higher energy density. But when butanol's price is at $4.7 and its carbon emission is also higher than those of bioethanols, the model decides not to produce any butanol, and the fuel portfolio will be the

[3] Based on a search on the butanol (mainly N-butanol) trade market.

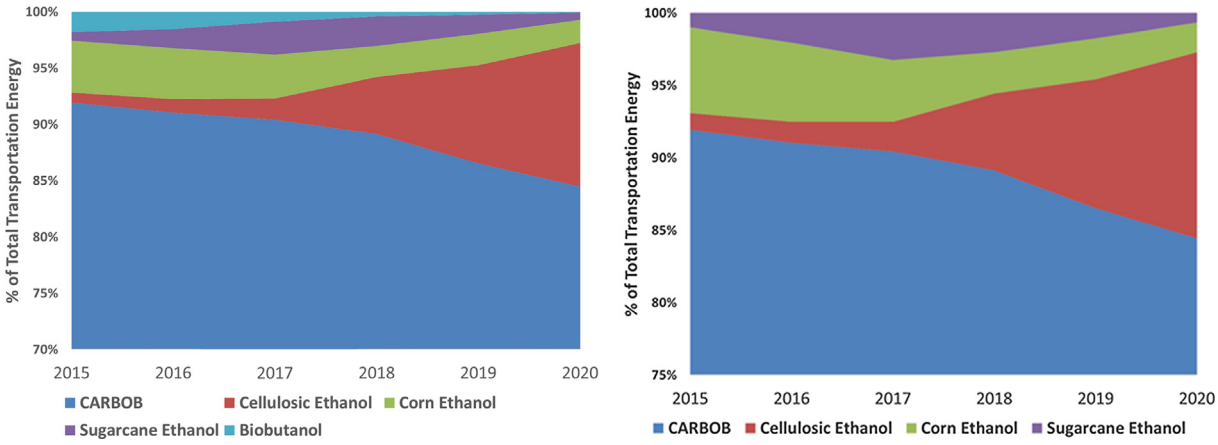

Fig. 5. Portfolio of gasoline and gasoline substitutes with biobutanol production costs at $3.1 (left) and $4.7 (right) per gallon.

same as shown in Fig. 2 (the case when butanol is not a fuel option). When butanol cost is $3.1 per gallon, it obtains some market share in the early years (2015–2017) and diminishes after 2018 when low carbon regulation is tightened. This result is expected. Butanol has high energy density and lower cost per MJ content; thus it gains advantages in the early years when the carbon intensity requirement is less stringent. Butanol's high carbon intensity leads to a carbon deficit and associated costs; therefore, after the year 2018, it diminishes.

5.5. Policy implications

We summarize some policy implications based on the modelling and findings of our study. It is worth noting that the implications are not only applicable to the Low Carbon Fuel Standard in California, but are also helpful to policy makers in other regions who are planning or evaluating the effectiveness of performance-based renewable energy policies to achieve environmental targets.

First, our results show that diesel fuels, particularly bio-based diesel fuels, are critical for successfully achieving a sustainable transportation energy portfolio. As shown in Fig. 1, the diesel fuel category provides the majority of carbon credits to satisfy average carbon intensity compliance. Specifically, the percentage of biodiesel blended into diesel fuel is projected to increase from 4% in 2015 (this was our model's prediction and actually observed in California [12]) to 20% in 2020, noting that 20% is the maximum share it can reach due to the biodiesel blend wall. It shows that the average carbon intensity for the diesel category is always lower than its carbon intensity compliance, but for the gasoline category this ratio is reversed. This difference calls for additional policies or regulations to facilitate advanced biodiesel production and usage. Particularly, most diesel engine warranties limit the use of diesel fuel containing less than 5% biodiesel [48]. Without lifting this warranty limit, biodiesel's large-scale adoption cannot be realized, and so neither can the environmental targets in transportation energy. Therefore, government efforts are needed to facilitate the certification of diesel engine performance running on diesel fuel with a high percentage of biodiesel.

Second, an appropriately-designed financial instrument can promote the production of low carbon technologies with robust market participation. In this study, we prove, through mathematical inference and empirical comparison, that there is a strong linkage between financial instrument, i.e. carbon credit price, and regulation, i.e. carbon intensity compliance, within a performance-based regulation framework. Through its designed financial instrument and market mechanism, this performance-based framework promotes the production of second-generation biofuel, cellulosic ethanol, which was not achieved by the technology-based regulation of the Renewable Fuel Standard. A similar relationship between financial instrument and regulation is also observed in other fields, such as in the power utility industry [59]. Therefore, modelling work is needed during the policy preparation stage to better design policies for achieving sustainability targets using a market approach.

Thirdly, biobutanol, as a promising biofuel, has high energy density (low cost per MJ energy content) as well as high carbon emissions per MJ. These features make it competitive when carbon intensity regulation is less strict. The low carbon regulation and carbon deficit cost will force butanol out of future fuel portfolios. Therefore, reducing carbon intensity is the key to promote butanol under a performance-based low carbon fuel policy. Some recent literature [60–62] analysed the life cycle of GHG emissions of butanol using various innovative processes and raw materials. If successful, biobutanol could be a promising biofuel in the future of the transportation sector.

6. Conclusions

The main contribution of this study is to establish a mathematical program with an equilibrium constraints model to investigate transportation energy market equilibrium under performance-based environmental regulations. Performance-based environmental regulation refers to policies such as California's Low Carbon Fuel Standard, which requires energy providers to reduce incrementally the carbon intensity of their fuels with any format of energy portfolio, rather than setting specific technological targets such as the Renewable Fuel Standard. In this study, the market equilibrium solutions are found by transferring each energy provider's profit maximization to Karush-Kuhn-Tucker optimality conditions. Profits through commodity trading and carbon trading are considered. This is the first study to simultaneously model the commodity market and the carbon trading market under performance-based environmental regulation. The findings of this study can help researchers and policy makers design performance-based regulations and evaluate the effectiveness of the carbon credit trading mechanism.

Our study confirms that reducing transportation greenhouse gas emissions requires a portfolio approach. The carbon credit trading market plays a critical role to economically promote the production of high cost, low emission, second-generation biofuel (i.e. cellulosic ethanol). The diesel fuel category, particularly biodiesel, is a major driver for reducing carbon emissions. In the gasoline fuel category, the annual production volume of cellulosic ethanol has to reach around 2 billion gallons by the end of 2020 in order to satisfy the most stringent compliance under the Low Carbon Fuel Standard. Although its production cost is the lowest among biomass-based fuels, corn ethanol's production volume is gradually reduced because of its high carbon intensity value. Sugarcane ethanol imports first increase then decrease after 2017, which proves its role as the interim solution to satisfy low

carbon fuel policy. The modeled carbon credit price is estimated to increase from around $60 per metric ton CO_2e in 2015 to $120 in 2019. The trend of carbon credit price is driven by carbon intensity compliance.

We validate our model results with actual data. Our model results, both for fuel production quantity and carbon credit price, match the trend of variation in actual data. However, the values fail to match exactly. One explanation is that our model does not allow carbon credit banking for use in future years, which is allowed in the actual market. This can impact the supply of carbon credit as well as its price. Other factors, such as carbon trade transaction costs, could also be responsible for the inconsistency of our model results with actual data.

We compare transportation energy portfolios under system least-cost and market equilibrium cases. The market equilibrium case produces more cellulosic ethanol than the system case, particularly for the early years. Implementing the carbon credit market encourages the production of cellulosic ethanol because of its potential revenue on carbon credit trading. In the meantime, less corn ethanol and sugarcane ethanol are produced/imported in the market equilibrium case compared to the system case. This is expected given that corn, sugarcane and cellulosic ethanol are competing for the 15% volume mandated to gasoline suppliers by the biofuel blend wall rule.

Our findings also lead to some policy implications. First, diesel fuels have great potential in de-carbonization and are critical to achieving a sustainable transportation energy portfolio. The majority of heavy-duty freight vehicles are using diesel fuels. It is easier to utilize government efforts to promote advanced biomass-based diesel fuels across the business sector compared to the passenger vehicle fleet, which involves distributed individual choices. Second, there is a strong link between financial instrument, i.e. carbon credit price, and regulation, i.e. carbon intensity compliance, within performance-based regulation. Detailed modelling work is needed during the policy preparation stage to better design policies for achieving sustainability targets using the market approach. Third, biobutanol is a promising biofuel in future transportation energy portfolios. Reducing carbon intensity is the key to promote biobutanol under performance-based low carbon fuel policies.

Future research can focus on relaxing some assumptions or constraints developed in this market equilibrium modeling framework. Examples are:

(1) Allowing the banking of carbon credits for future trading or using other financial instruments to fully leverage the advantages of advanced low carbon biofuels in order to encourage its production;
(2) Having multiple fuel suppliers and adding spatial characteristics of fuels into our model. The production location of biofuel significantly influences its carbon footprint. Adding these spatial features can improve the representativeness of our model to the real market.
(3) Investigating government control mechanisms, such as provide carbon price guidance, to maximize social welfare. Clearly, the current market equilibrium model is not system optimal. Methods should be developed to help the government manage and guide renewable energy policies to achieve optimal social welfare.

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References

[1] International Energy Agency Statistics. CO2 emissions from fuel combustion-highlights 2015 Edition. Paris, France: International Energy Agency; 2015. https://www.iea.org/publications/freepublications/publication/co2-emissions-from-fuel-combustion—2015-edition—excerpt.html [accessed on July 13th, 2016].
[2] Borken-Kleefeld J, Chen Y. Vehicle emission deterioration – results from long term high volume on-road measurements. Atmos Environ 2015;101:58–64.
[3] Chen Y, Borken-Kleefeld J. Real-world emissions from cars and light trucks – results from 12 years remote sensing at Zurich/CH. Atmos Environ 2014;88:76–82.
[4] Cheng YH, Chang YH, Lu IJ. Urban transportation energy and carbon dioxide emission reduction strategies. Appl Energy 2015;157:953–73.
[5] Dai H, Xie X, Xie Y, Liu J, Masui T. Green growth: the economic impacts of large-scale renewable energy development in China. Appl Energy 2016;162:435–49.
[6] Chalvatzis KJ, Ioannidis A. Energy supply security in the EU: benchmarking diversity and dependence of primary energy. Appl Energy 2017;207:465–76.
[7] Bai Y, Ouyang Y, Pang JS. Biofuel supply chain design under competitive agricultural land use and feedstock market equilibrium. Energy Econ 2012;34(5):1623–33.
[8] Whistance J, Thompson W, Meyer S. Interactions between California's low carbon fuel standard and the national renewable fuel standard. Energy Policy 2017;101:447–55.
[9] California Air Resource Board. Proposed Regulation to Implement Low Carbon Fuel Standard Volume I & II. Low Carbon Fuel Standard Program. Sacramento, CA; 2009.
[10] Ekins P, Drummond P, Görlach B. Policy instruments for low-carbon development based on work from the EUFP7 project, CECILIA2050: combining policy instruments to achieve Europe's 2050 climate targets; 2017.
[11] Du J, Ouyang D. Progress of Chinese electric vehicles industrialization in 2015: a review. Appl Energy 2017;188:529–46.
[12] Yeh S, Witcover J, Lade GE, Sperling D. A review of low carbon fuel policies: principles, program status and future directions. Energy Policy 2016;97:220–34.
[13] Coglianese C, Nash J, Olmstead T. Performance-based regulation: prospects and limitations in health, safety and environmental protection. Admin L Rev 2003;4:705.
[14] Luo Z-Q, Pang J-S, Ralph D. Mathematical programs with equilibrium constraints. Cambridge University Press; 1996. ISBN 0-521-57290-8.
[15] Kuhn HW, Tucker AW. "Nonlinear programming". In: Proceedings of 2nd Berkeley symposium. Berkeley: University of California Press; 1951. p. 481–492. MR 0047303.
[16] May PJ. Performance-based regulation and regulatory regimes: the saga of leaky buildings. Law & Policy 2003;25(4):381–401.
[17] Wesseling JH, Farla JCM, Hekkert MP. Exploring car manufacturers' responses to technology-forcing regulation: the case of California's ZEV mandate. Environmental Innovation and Societal Transitions 2015;16:87–105.
[18] US Government Accountability Office. Renewable Fuel Standard: Program Unlikely to Meet Its Targets for Reducing Greenhouse Gas Emissions. Report to the Chainman, Subcommittee on Regulatory Affairs and Federal Management, Committee on Homeland Security and Governmental Affairs, U.S. Senate.GAO-17-94, November, 2016; 2016.
[19] Coglianese C, Nash J, Olmstead T. Performance-based regulation: prospects and limitations in health, safety and environmental protection. RPP-03, Regulatory Policy Program. Center for Business and Government, John F. Kennedy School of Government, Harvard University; 2002.
[20] Banos R, Manzano-Agugliaro F, Montoya FG, Gil C, Alcayde A, Gomez J. Optimization methods applied to renewable and sustainable energy: a review. Renew Sustain Energy Rev 2011;15(4):1753–66.
[21] Tyner W, Taheripour F. Biofuels, policy options, and their implications: analyses using partial and general equilibrium approaches. J Agric Food Ind Organ 2008;6(2).
[22] Rajagopal D, Sexton S, Hochman G, Roland-Holst D, Zilberman D. Model estimates food-versus-biofuel trade-off. Calif Agric 2009;63(4). 199(3).
[23] Chen X, Huang H, Khanna M, Onal H. Meeting the mandate for biofuels: implications for land use, greenhouse gas emissions and social welfare. In: Proceedings of the NBER meeting on agricultural economics and biofuels, April 2010; 2010.
[24] Yue D, You F, Snyder SW. Biomass-to-bioenergy and biofuel supply chain optimization: overview, key issues and challenges. Comput Chem Eng 2014;66:36–56.
[25] Chen Y, Fan Y. Transportation fuel portfolio design under evolving technology and regulation: a California case study. Transp Res Part D: Transp Environ 2013;24:76–82.
[26] Chen Y, Fan Y. Coping with technology uncertainty in transportation fuel portfolio design. Transp Res Part D: Transp Environ 2014;32:354–61.
[27] Moncada JA, Junginger M, Lukszo Z, Faaij A, Weijnen M. Exploring path dependence, policy interactions, and actor behavior in the German biodiesel supply chain. Appl Energy 2017;195:370–81.
[28] Jin Y, Illukpitiya P. Cost minimization of supplying biomass for ethanol biorefineries. Energy 2016;96:209–14.
[29] Zhai M, Zhang X, Cheng F, Zhou X, Su X. A game-theoretic analysis of the government's role on the biomass supply chain construction. Int J Ambient Energy 2017;38:444–58.
[30] Huang S, Hu G. Biomass supply contract pricing and environmental policy analysis: a simulation approach. Energy 2018;145:557–66.
[31] Chen Y, Zhang Y, Fan Y, Hu K, Zhao J. A dynamic programming approach for modeling low-carbon fuel technology adoption considering learning-by-doing effect. Appl Energy 2017;185(1):825–35.
[32] McPhail LL, Babcock BA. Ethanol, mandates, and drought: insights from a stochastic equilibrium model of the U.S. Corn Market. Working Paper. Center for Agricultural and Rural Development, Iowa State University; 2008.
[33] Thompson W, Meyer S, Westhoff P. How does petroleum price and corn yield volatility affect ethanol markets with and without an ethanol use mandate? Energy Policy 2009;37(2):745–9.
[34] Lapan H, Moschini G. Second-best biofuel policies and the welfare effects of

quantity mandates and subsidies. J Environ Econ Manage 2012;63(2):224–41.
[35] Chen X, Li L. Supply of cellulosic biomass in Illinois and implications for the Conservation Reserve Program. Global Change Biol, Bioenergy 2016;8:25–34.
[36] Mason CF, Wilmot NA. Price discontinuities in the market for RINs. J Econ Behav Organ 2016;132(B):79–97.
[37] Huang Y, Chen Y. Analysis of an imperfectly competitive cellulosic biofuel supply chain. Transp Res Part E: Logistics Transp Rev 2014;72:1–14.
[38] The Conference Board of Canada. Renewable Fuel Standards Within a Low-Carbon Fuel Strategy; 2016. http://ricanada.org/wp-content/uploads/2017/09/9115-Renewable-Fuel-Standards_BR.pdf.
[39] Hill N, Bates J. Europe's Clean Mobility Outlook: Scenarios for the EU light-duty vehicle fleet, associated energy needs and emissions, 2020–2050; 2018. Available at https://epure.org/media/1729/ed51122_epure_cmp_modelling_final-report_issue3.pdf.
[40] Ahlgren EO, Börjesson Hagberg M, Grahn M. Transport biofuels in global energy–economy modelling–a review of comprehensive energy systems assessment approaches. GCB Bioenergy 2017;9(7):1168–80.
[41] Bromberg L, Cheng WK. Methanol as an alternative transportation fuel in the US: options for sustainable and/or energy-secure transportation. Cambridge (MA): Sloan Automotive Laboratory, Massachusetts Institute of Technology; 2010.
[42] Ratcliff MA, Luecke J, Williams A, Christensen E, Yanowitz J, Reek A, et al. Impact of higher alcohols blended in gasoline on light-duty vehicle exhaust emissions. Environ Sci Technol 2013;47(23):13865–72.
[43] da Silva Trindade WR, dos Santos RG. Review on the characteristics of butanol, its production and use as fuel in internal combustion engines. Renew Sustain Energy Rev 2017;69:642–51.
[44] EIA. U.S. Monthly Energy Review. United States, Washington, D.C.: Energy Information Agency, Department of Energy; 2018. Available at https://www.eia.gov/totalenergy/data/monthly/index.php#renewable.
[45] Anderson JD, Coble KH. Impact of renewable fuels standard ethanol mandates on the corn market. Agribusiness 2010;26(1):49–63.
[46] CARB. Draft Vision 2.0 Modeling System: General Model Documentation. California Air Resource Board; 2015. Available at https://www.arb.ca.gov/planning/vision/docs/vision2.0lr_model_documentation.pdf.
[47] California Air Resource Board. Low Carbon Fuel Standard Lookup Tables. Low Carbon Fuel Standard Program. Sacramento, CA; 2009.
[48] Automakers' and Engine Manufacturers' positions of Support for Biodiesel Blends. Biodiesel.org. http://biodiesel.org/using-biodiesel/oem-information/oem-statement-summary-chart [accessed on July 10th, 2018].
[49] US Census Bureau. Energy and utility: prices, expenditures. Washington, DC: US Census Bureau; 2017.
[50] Zhang Y, Joshi S, MacLean H. Can ethanol alone meet California's low carbon fuel standard? An evaluation of feedstock and conversion alternatives. Environ Res Lett 2010;5:1–14.
[51] IEA. Technology roadmap – delivering sustainable bioenergy. Paris, France: International Energy Agency; 2017.
[52] Energy Information Administration. Electricity prices reflect rising delivery costs, declining power production costs. Washington, DC: Energy Information Administration, US Department of Energy; 2017.
[53] NREL. Hydrogen Production Cost Analysis Map. Golden (Colorado): National Renewable Energy Laboratory; 2011 [accessed at https://www.nrel.gov/hydrogen/production-cost-analysis-text.html].
[54] Energy Information Administration. Annual Energy Outlook. Washington, DC: Energy Information Administration, US Department of Energy; 2017.
[55] Fourer R, Gay DM, Kernighan BW. AMPL: a modeling language for mathematical programming. 2nd ed. The Scientific Press; 2003.
[56] ARKI. Using CONOPT with AMPL. ARKI Consulting and Development.
[57] Wu M, Wang M, Liu J, Huo H. Assessment of potential life-cycle energy and greenhouse gas emission effects from using corn-based butanol as a transportation fuel. Biotechnol Prog 2008;24(6):1204–14.
[58] Jiang Y, Liu J, Jiang W, Yang Y, Yang S. Current status and prospects of industrial bio-production of n-butanol in China. Biotechnol Adv 2015;33(7):1493–501.
[59] Sappington DE, Pfeifenberger JP, Hanser P, Basheda GN. The state of performance-based regulation in the US electric utility industry. Elect J 2001;14(8):71–9.
[60] Levasseur A, Bahn O, Beloin-Saint-Pierre D, Marinova M, Vaillancourt K. Assessing butanol from integrated forest biorefinery: a combined techno-economic and life cycle approach. Appl Energy 2017;198:440–52.
[61] Baral NR, Quiroz-Arita C, Bradley TH. Uncertainties in corn stover feedstock supply logistics cost and life-cycle greenhouse gas emissions for butanol production. Appl Energy 2017;208:1343–56.
[62] Pereira LG, Dias MOS, Mariano AP, Maciel Filho R, Bonomi AMFLJ. Economic and environmental assessment of n-butanol production in an integrated first- and second-generation sugarcane biorefinery: fermentative versus catalytic routes. Appl Energy 2015;160:120–31.